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10/657,210	09/09/2003	Larry Manevitz	26560	9148

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EXAMINER	
CALDWELL, MICHAEL J	
ART UNIT	**PAPER NUMBER**
2129	

DATE MAILED: 03/02/2006

Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No.	Applicant(s)
	10/657,210	MANEVITZ ET AL.
	Examiner	Art Unit
	Michael Caldwell	2129

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE _3_ MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on _09 September 2003_.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☐ Claim(s) _____ is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) _1-19_ is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☒ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on _08 March 2004_ is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application (PTO-152)
6) ☐ Other: _____.

DETAILED ACTION

1. This office action is responsive to application 10/657,210 filed September 9th, 2003. Claims 1-19 have been examined.

2. Receipt is acknowledged of papers submitted March 8th, 2004: Response to pre-exam formalities, including editing figures' numbers/letters/reference characters to meet size requirements pursuant to 37 C.F.R. 1.84 and 37 C.F.R. 1.121.

Specification

Applicant is reminded of the proper language and format for an abstract of the disclosure:

The abstract should be in narrative form and generally limited to a single paragraph on a separate sheet within the range of 50 to 150 words. It is important that the abstract not exceed 150 words in length since the space provided for the abstract on the computer tape used by the printer is limited. The form and legal phraseology often used in patent claims, such as "means" and "said," should be avoided. The abstract should describe the disclosure sufficiently to assist readers in deciding whether there is a need for consulting the full patent text for details.

The language should be clear and concise and should not repeat information given in the title. It should avoid using phrases which can be implied, such as, "The disclosure concerns," "The disclosure defined by his invention," "The disclosure describes," etc.

3. The abstract of the disclosure is objected to because improper claim language. Correction is required. See MPEP § 608.01(b).

Claim Objections

4. Claims 5-6 are objected to because of the following informalities: These claims state "...from said neural network parts," where the claims from which 5 and 6 depend only mention a singular neural network part. The examiner has assumed for the rest of the prosecution of this application that these claims meant to recite a singular neural network part, however, appropriate correction is required.

Regarding claim 16:

5. Claim 16 is objected to as being dependent upon a rejected base claim, but would be allowable if rewritten in independent form including all of the limitations of the base claim and any intervening claims.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

6. Claims 1-8, 10-15, and 17-19 are rejected under 35 U.S.C. 103(a) as being unpatentable over Manevitz et al. (*Finite-Element Mesh Generation Using Self-Organizing Neural Networks*, Computer-Aided Civil & Infrastructure Engineering, July 1997, Vol. 12 Issue 4, page 233; herein referred to as Manevitz) in view of Chedid et al. (IEEE Transactions on Magnetics: Vol. 32, No. 5, September 1996; herein referred to Chedid).

Regarding claim 1:

Manevitz teaches an apparatus for calculating numerical solutions for partial differential equations in successive intervals using adaptive meshes and where said mesh adaptively refines itself about emerging regions of complexity as said partial differential equation progresses over said successive intervals:

> Neural networks are applied to the problem of **mesh placement** for the finite-element method. When the **finite element method** is used to numerically solve a **partial differential equation** with **boundary conditions** over a domain, the domain must be divided into "elements." **(abstract, lines 1-5) (Manevitz)**
>
> ...
>
> The mesh should be finer in regions where the solution is believed to be **changing rapidly** or to have large gradients. Thus smaller elements should be used near singularity points such as reentrant corners or cracks, near holes, near small features of the boundary, near the location of **rapidly changing boundary data**, at and near inhomogeneities, etc. **(§1, ¶6, subsection 1) (Manevitz)**

Manevitz fails to teach using the neural net to produce predictions of values of a parameter following intervals based on values of said parameter available from previous intervals.

Chedid teaches a neural network part for producing predictions of values of a parameter at a following interval based on values of said parameter available from previous intervals.

> a **prediction of mesh density** is accomplished by a simple feedforward neural network which has the ability to learn the relationship between mesh density and model geometric features. It will be shown that ANN are **able to recognize delicate areas (abstract, lines 14-18) (Chedid)**
>
> ...
>
> a technique to predict the mesh density distribution, based on artificial neural networks. The basis is the fact that **these networks have the ability to learn from examples and to generalize**. It will be shown that a simple **feedforward ANN** is a suitable candidate, and **that reduction in both computation**

> **time and complexity** can be achieved through the introduction of the layer-by-layer approach, which will be described later in Section IV-C. The predicted mesh density function can then be used in conjunction with a density-driven software [3] , [5] or, as will be shown in Part II of this paper, **sent to a Kohonen network to predict the final mesh (§ 1, ¶ 3, lines 22-33) (Chedid)**

It would have been obvious for one of ordinary skill in the art at the time of applicant's invention to have combined Manevitz's neural network approach to a finite element method (FEM) application of solving partial differential equations (PDEs) with Chedid's predictive feedforward neural network (also specifically a Kohonen network) to considerably hasten computation of the next adaptation of the mesh as applied to the domain of the solution to the PDE. Applicant has admitted the community awareness of such a system. Both neural networks being used for prediction of values of a parameter at a following interval based on values of said parameter available from previous intervals, and adaptive meshing through FEM of PDEs are known to have existed prior to applicant's invention. Therefore, combining the predictive behavior of such ANNs to look ahead in the FEM thereby reducing computation time would have been obvious to one of ordinary skill in the art.

<u>Regarding claim 2:</u>

Manevitz discloses the limitations of claim 2 wherein said successive intervals are time intervals. The successive intervals are the discretized "rapidly changing data" **(§1, subsection 1) (Manevitz)** about which the regions corresponding to the mesh Manevitz discloses should be finer to capture the more interesting and detailed data.

Regarding claim 3:

Manevitz discloses the limitations of claim 3 wherein said parameter is a gradient.

> The mesh should be finer in regions where the solution is believed to be changing rapidly or to have large **gradients**. **(§ 1, subsection 1) (Manevitz)**

Regarding claim 4:

Manevitz discloses the limitations of claim 4 wherein said mesh adaptation part is further configured to adaptively coarsen said mesh about regions of low complexity:

Manevitz mentions a need to have the mesh finer in regions of high complexity and that it should not be uniform, and also mentions the high computational cost of rendering such detailed information (§1, ¶5), wherein said mesh adaptation part is further configured to adaptively coarsen said mesh about regions of low complexity.

> Of course, the density of the mesh should not necessarily be uniform. The mesh may be finer in some regions and coarser in others ... Thus the actual density of the mesh used in a certain computation is a compromise between accuracy and cost. ... The mesh may be finer in some regions and coarser in others.
> **(§ 1, ¶ 5) (Manevitz)**

The common trade-off of computation cost and resource expenditure for accuracy and precision has been common in computer science since its beginnings as well as elsewhere. It would have been obvious for one of ordinary skill in the art at the time of applicant's invention to employ techniques to minimize the computation cost and make efficient use of limited resources, such techniques including but not limited to coarsening the mesh density and thus somewhat alleviating intensive data processing.

Regarding claims 5 and 6:

Manevitz discloses the limitations of claims 5 and 6, wherein said mesh adaptation part comprises a first/second thresholder for thresholding gradients from said neural network part~~(s)~~, such that gradients above/below said threshold value are taken to indicate complexity and to lead to local refining/coarsening of said mesh (respectively) (see above quote from Manevitz, §1, 5).

Examiner holds thresholding to be inherent in automatically and quantitatively classifying elements to be either refined or coarsened. Application of the gradient as the signaling characteristic would be an obvious choice of stated thresholders to one of ordinary skill in the art, as a gradient is a measure of the rate of change of some quantitative property, which is ideal for the purpose of determining regions of complexity.

Regarding claim 7:

Manevitz and Chedid teach the limitations of claim 1 for the reasons above, and in addition Chedid discloses the limitations of claim 7 wherein said neural network part comprises two neural networks, each having an input layer of input elements, at least one hidden layer of hidden elements and an output layer of at least one output element, said two neural networks differing from each other in respective numbers of input elements.

Examiner holds this configuration of neural networks wherein having an input layer of input elements, at least one hidden layer of hidden elements and an output layer of at least one output element, to be standard of innumerable types of neural networks containing a hidden layer (feedforward, recurrent, radial-basis-function, etc) and is by no means novel to one of ordinary skill in the art at the time of applicant's invention.

> The network consists of **an input layer, one or more hidden layers, and an output layer** [8]. Signals flow into the input layer, pass through the hidden layer, and arrive at the output layer. **(§ IV, subsection B, lines 1-4) (Chedid)**

This configuration wherein 2 neural networks differ from each other in respective numbers of input elements is an example of robustness for similar tasks, as well as parallel computation for potentially either similar or different tasks.

Regarding claim 8:

Manevitz and Chedid teach the limitations of claim 1 for the reasons above, and in addition Chedid discloses the limitations of claim 8, wherein each hidden element defines a hyperbolic tan-sigmoid transfer function.

Manevitz fails to teach the apparatus of claim 7 wherein each hidden element defines a hyperbolic tan-sigmoid transfer function. This is a common and flexible transfer function with which to bound the hidden layer node's input.

Chedid discloses a neural network wherein each hidden element defines a hyperbolic tan-sigmoid transfer function: (a hyperbolic tan-sigmoid transfer function function is a sigmoid function)

> The network consists of an **input layer, one or more hidden layers, and an output layer** [8]. Signals flow into the input layer, pass through the hidden layer, and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by the interconnect values between neurons. The neuron then produces its output signal by passing the summed signal through **a sigmoid function**. **(§ IV, subsection B, lines 1-9) (Chedid)**

Regarding claim 10:

Manevitz discloses the limitations of claim 10, wherein a first of said neural networks is a boundary element neural network for calculating gradients of boundary elements of said adaptive mesh, and a second of said neural networks is an interior element neural network for calculating gradients of interior elements of said adaptive mesh.

> One novelty of the method is the interweaving of versions of the Kohonen algorithm in different dimensions simultaneously in order to handle the **boundary of the domain** properly. **(abstract, 2nd ¶) (Manevitz)**
>
> ...
>
> For our application, it is important that eventually the network , i.e., **that boundary points of the network fall on boundaries of the domain**. The basic Kohonen map does not typically fulfill this constraint. For example, for the body in Fig. 5, the result is as in Fig. 6. This constraint resulted in the implementation of some heuristic rules and the interweaving of several Kohonen algorithms together... **(§ 3.2.3) (Manevitz)**
>
> ...
>
> In order to **distribute the points appropriately on the boundary** (but after the net has reached the boundary), we apply a Kohonen algorithm to this one-dimensional simplex. **(§3.2.4, ¶ 3) (Manevitz)**
>
> ...
>
> In addition, once a point is on the **boundary**, we do not allow it to leave the boundary (as might occur from the two dimensional algorithm); in effect, **the two-dimensional algorithm now acts only on the interior of the original net**. **(§ 2 - § 3) (Manevitz)**

The claimed first boundary element neural network for calculating gradients of boundary elements of said adaptive mesh, and a second of said neural networks is an interior element neural network for calculating gradients of interior elements of said adaptive mesh are the disclosed "self-organizing algorithm of Kohonen [which] is adapted to solve the problem of automatically assigning (in a near-optimal way) coordinates from a two-dimensional domain to a given topologic grid (or mesh) of nodes in order to apply the finite element method effectively when solving a partial differential equation with boundary conditions over that domain." **(Manevitz, abstract, ¶1)**

Regarding claim 11:

Manevitz discloses the limitations of claim 11, wherein said boundary element neural network has fewer input elements than said interior element neural network.

> In other words, the **neural network becomes a representative map of the sample data information**. This is exploited by us, in order to arrange for the placement of the finite-element mesh, by identifying the mesh nodes with neural nodes and identifying the weight space with the physical space of the domain, thereby **causing the network to be an approximation of the density function. (§ 2, ¶ 7) (Manevitz)**

Therefore, the amount of input elements is proportional to the effort expended in applying the mesh to either the boundary or the interior. Since there are many more interior nodes than boundary nodes, the boundary element neural network necessitates having fewer input elements than the interior element neural network.

Regarding claim 12:

Manevitz discloses the limitations of claim 12, wherein said input elements are connected to gather for a given mesh element a gradient of said mesh element, and a gradient of each neighboring element for each of a current and a previous interval.

> The location of the chosen node is adjusted, as is the coordinates of all nodes **within a certain neighborhood of this chosen node**. **(§ 3.1, subsection 4) (ALSO Figure 1) (Manevitz)**
>
> ...
>
> The **mesh should be finer in regions where the solution is believed to be changing rapidly or to have large gradients**. Thus smaller elements should be used near singularity points such as reentrant corners or cracks, near holes, near small features of the boundary, near the location of **rapidly changing boundary data**, at and near inhomogeneities, etc. **(§ 1, ¶ 6, subsection 1) (Manevitz)**

Applicant is reminded of the herein discussed intervals in the rejection of claim 1.

Regarding claim 13:

Manevitz discloses the limitations of claim 13, wherein each hidden element defines a hyperbolic tan-sigmoid transfer function, each output element defines a linear transfer function, a first of said neural networks is a boundary element neural network for calculating gradients of boundary elements of said adaptive mesh, and a second of said neural networks is an interior element neural network for calculating gradients of interior elements of said adaptive mesh, and said boundary element neural network has fewer input elements than said interior element neural network.

Claim 13 is rejected since its limitations are the sum of dependent claims 8 through 11, all of which have been separately and individually rejected for reasons mentioned above. The rejections when taken together stand as a similar rejection for claim 13. Please see aforementioned rejections.

Regarding claims 14 and 15:

Manevitz discloses the limitations of claims 14 and 15 wherein said interior element neural network comprises eight input elements, six hidden elements and one output element and wherein said boundary element neural network comprises six input elements, six hidden elements and one output element.

> The network consists of an **input layer, one or more hidden layers, and an output layer** [8]. Signals flow into the input layer, pass through the hidden layer, and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by the interconnect values between neurons. The neuron then produces its output signal by passing the summed **signal through a sigmoid function [8].** In this work, the network (see Fig. *5)* consists of an input layer of **eight processing units, one hidden layer of 12 processing units, and an output layer of one processing unit**. **(§ IV, subsection B: Architecture) (Chedid)**

Regarding claim 18:

Manevitz discloses a method of adapting a finite element mesh **(abstract, ¶1, lines 1-2, 5)** interactively with calculations of numerical solutions for a partial differential equation **(abstract, ¶1, lines 2-5)** in successive intervals **(§1, ¶6, subsection 1)**, said partial differential equation being calculated over a domain in accordance with respective finite elements of said mesh **(abstract, ¶1, lines 2-5)**, each successive interval using a further adaptation of said mesh **(abstract, ¶3, lines 3-5)**, the method comprising:

producing predictions of values of a parameter of said partial differential equation at mesh elements **(§1, ¶6, subsection 1)** at a following interval based on values of said parameter available from previous intervals,

and adapting said mesh over said domain of a respective partial differential equation using said predictions, such that said mesh adaptively refines itself about emerging regions of complexity **(abstract, ¶3, lines 3-5)**, as said partial differential equation progresses over said successive intervals.

Manevitz fails to teach using the neural net to produce predictions of values of a parameter following intervals based on values of said parameter available from previous intervals or said neural network adapting said mesh over a domain of a respective partial differential equation *using said predictions.*

Chedid teaches a neural network that produces predictions of values of a parameter at a following interval based on values of said parameter available from previous intervals **(abstract, ¶ 1, lines 14-18, neural network prediction requires previous data, or training data, for successful generalization)** and having the neural network adapt said mesh over a domain using said predictions.

Regarding claim 19:

Manevitz discloses the limitations of claim 19 wherein said parameter is a gradient.

> For example, **it is expected that the solution exhibits high gradients near a sharp corner in the boundary**. In such cases, **a density function may be chosen to exploit this information**. If nothing is known a priori about the solution, a density function may still be chosen in an adaptive a posteriori

> fashion. For example, the problem may be solved preliminarily with a uniform-density mesh (perhaps with relatively few nodes), and then a **density function may be constructed based on the gradients of this solution prior to resolving it**. (In our examples we chose the density function by hand, with the knowledge of the available exact solutions.) **(§ 2, ¶ 5, 13-24) (Manevitz)**

Claim Rejections - 35 USC § 103

7. Claim 9 is rejected under 35 U.S.C. 103(a) as being unpatentable over Manevitz and Chedid as applied to claims 1 and 7 above, and in further view of Hassoun (*Fundamentals of Artificial Neural Networks*, MIT Press, 1995).

Manevitz and Chedid fail to teach the apparatus according to claim 9, wherein each output element defines a linear transfer function.

Hassoun teaches a single-hidden-layer net with both sigmoidal activation units (of claim 8) and wherein each output element defines a linear transfer function:

> The most important feature that distinguishes the RBF network from earlier radial basis function-based models is its adaptive nature, which generally allows it to utilize a relatively smaller number of locally tuned units (RBFs). ... The RBF network has a feedforward structure consisting of a single hidden layer of *J* locally tuned units which are fully interconnected to **an output layer of *L* linear units**, as shown in Figure 6.1.1. **(§ 6.1, page 286) (Hassoun)**

It would have been obvious for one of ordinary skill in the art at the time of applicant's invention to have combined the linear output transfer function of Hassoun with Manevitz and Chedid's automatic finite element mesh generation procedures to utilize the benefits of radial-basis-function neural networks, including but not limited to accelerated training (when compared to backpropagation neural networks).

Claim Rejections - 35 USC § 103

8. Claim 17 is rejected under 35 U.S.C. 103(a) as being unpatentable over Manevitz as applied to claim 16 above, and further in view of Lagaris et al. (Artificial Neural Networks for Solving Ordinary and Partial Differential Equations, IEEE Transactions On Neural Networks, Vol. 9, No. 5, September 1998; herein referred to as Legaris).

Manevitz and Chedid fail to teach the apparatus according to claim 17, wherein said neural network part is configured for training using the Levenberg Marquardt training method.

Legaris discloses a neural network wherein said neural network part is configured for training using the Levenberg Marquardt training method.

> Once the derivative of the error with respect to the network parameters has been defined it is then straightforward to **employ almost any minimization technique**. For example it is possible to use either the **steepest descent** (i.e., the **backpropagation algorithm** or any of its variants), or the conjugate gradient method or other techniques proposed in the literature. In our experiments we have employed the quasi-Newton BFGS method [9] **(§ II, subsection *A: Gradient Computation*, ¶5) (Legaris)**

It would have been obvious for one of ordinary skill in the art at the time of applicant's invention to apply the Levenberg Marquardt training method to improve the speed of convergence to local minima while also escaping shallow local minima, which generally leads to better solution quality. (See Hassoun, page 218)

Conclusion / Correspondence Information

9. Claims 1-15, 17-19 are rejected.

10. The prior art made of record and not relied upon is considered pertinent to applicant's disclosure:

- Jerome T. Connor, R. Douglas Martin, L. E. Atlas; Recurrent Neural Networks and Robust Time Series Prediction; IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. *5*, NO. 2, MARCH 1994
- Mike L. Forcada; Neural Networks: Automata and Formal Models of Computation; January 21, 2002; http://www.dlsi.ua.es/~mlf/nnafmc/ (available June 5th 2002)
- D. A. Lowther; On Automatic Mesh Generation using Kohonen Maps; IEEE TRANSACTIONS ON MAGNETICS, VOL 34, NO. 5, SEPTEMBER 1998
- D. G. Triantafyllidis & D. P. Labridis; An Automatic Mesh Generator For Handling Small Features In Open Boundary Power Transmission Line Problems Using Artificial Neural Networks; *Commun. Numer. Meth. Engng.* 2000; 16:177-190
- D. Gobovic and M.E. Zaghloul; Analog Cellular Neural Network With Application to Partial Differential Equations With Variable Mesh-Size

11. Any inquiry concerning this communication or earlier communications from the examiner should be directed to Michael Caldwell whose telephone number is (571) 272-1942. The examiner can normally be reached on Mon-Fri 10:00-6:00.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, David Vincent can be reached on (571) 272-3080. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free).

MJC

2/16/06
DAVID VINCENT
SUPERVISORY PATENT EXAMINER